Human Motion Recognition Method in Physical Education Based on Wearable Perception

Pengli Liu(✉) and Zhiqiang Wang

Sports Center, Xian Eurasia University, Xian 710000, China
liupengli7563@163.com

Abstract. The traditional human behavior recognition technology takes a long time to recognize human behavior. Aiming at the shortcomings of traditional methods, this paper designs a new human action recognition method in physical education based on efficient wearable sensor network. Firstly, the human action recognition characteristics of physical education teaching are extracted. Secondly, the human action recognition model of physical education teaching is constructed based on wearable perception, so as to realize human action recognition. The results show that the shortest action recognition time of physical education teaching people designed in this paper is 0.169 s. The designed physical education teaching human action recognition method has good recognition effect and certain application value.

Keywords: Wearable perception · Physical education · Human body · Action recognition

1 Introduction

As an advanced information processing tool, computer has provided information services for mankind since its birth. In recent years, with the continuous improvement of hardware manufacturing and software development technology, all kinds of miniaturized devices with communication, perception and computing capabilities have become popular [1]. The services provided by computers have also changed from the original proprietary and centralized computing services to more flexible services around people's needs. Computing systems and human users are more closely combined through natural interaction [2–4]. In this kind of computer system, an important supporting technology is the perception and recognition technology of human behavior, so that it can provide services according to human behavior [5]. On the basis of human behavior recognition, a series of typical applications can be developed. In academic circles, a lot of research has also been carried out on the development of such a new application system [6]. To realize human behavior recognition, we must solve many problems, including human behavior perception, behavior modeling and recognition. In perception, we should not only capture the data related to human behavior, but also provide a good user experience [7]. In modeling and recognition, we should fully consider the complexity of human behavior

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and meet the application requirements in performance [8]. Human behavior recognition technology has attracted extensive attention in academia and industry because of its broad application prospects and rich research problems. Under this background, this paper makes a systematic and in-depth research on human behavior recognition in daily life.

Despite the support of rich perceptual means and computing resources, it is still a challenge to realize the recognition of human behavior [9]. Firstly, from the perspective of behavior perception, what type of data can best reflect the characteristics of behavior and is most conducive to subsequent recognition is still an unsolved problem. Secondly, from the perspective of perception methods, how to reduce the interference to people's daily life as much as possible on the basis of ensuring that the perceived data can be effectively used for behavior recognition Protecting people's privacy and improving the wearing experience [10] is still a very challenging problem; Third, from the perspective of human behavior, people's daily behavior is complex, the implementation of behavior is arbitrary, and there is complex interaction between people. How to model complex behaviors and identify them accurately is a very difficult problem; Finally, in some application scenarios, there are performance requirements represented by real-time performance of the recognition system. How to give consideration to the accuracy and performance of recognition at the same time needs to be deeply studied. Therefore, how to realize real-time human behavior recognition technology for complex behavior based on wearable sensor network is a problem worthy of research. The research on Chinese elementary mathematical knowledge extraction based on CRF algorithm proposed in document [11] introduces the traditional CRF process of named entity recognition. Then, an improved algorithm CRF++ for conditional field model is proposed. Aiming at the low recognition rate of named entities based on traditional machine learning methods, a post-processing method of entity recognition with automatic dictionary generation is proposed. After identifying mathematical entities, a pruning strategy combining Viterbi algorithm and rules is proposed to improve the recognition rate of basic mathematical entities. The distribution and application of the main additional error in the fractal coding method proposed in reference [12]. By extracting the original additional error value, a new fast fractal coding method is proposed. Then, using the extracted main additional error values, we analyze the distribution of these values. We found that different distributions of values represent different parts of the image. Finally, we analyze the experimental results and find some properties of these values. Experimental results also show the effectiveness of this method. And the existing human motion recognition methods have not been applied to physical education teaching, which cannot ensure the recognition accuracy and recognition performance on the basis of ensuring that the perceptual data is effectively applied to sports motion recognition.

In order to solve the above problems, this paper systematically studies the human behavior recognition technology in physical education teaching based on wearable sensor network. Aiming at the complexity of human behavior, the problem of behavior recognition in the case of single person complex behavior execution is deeply studied. Various data related to human behavior are obtained through various sensing means contained in wearable sensor networks, and the corresponding human behavior is recognized through behavior model based on behavior recognition algorithm. The recognition algorithm based on EP and ESP is used to accurately segment the boundary between adjacent behaviors. The recognition of multi - person interaction behavior is studied from the perspective of group From the perspective of behavior recognition system performance, the problem of real-time behavior recognition is studied. From the perspective of perception means, the low-cost maintenance free human behavior perception technology based on passive wearable devices is studied.

2 Design of Human Motion Recognition Method in Physical Education Teaching Based on Wearable Perception

2.1 Extracting Human Motion Recognition Features in Physical Education Teaching

Recognition is one of the most frequent activities of human beings and other living bodies in their life. It is a basic ability that human beings must have to know, understand and adapt to the environment. In the above understanding, not as a special mode of observation methods and concluded that the provisions of the observation can be through biological capacity, such as eye view, hear, touch to get the feeling in the form of observations, can also is to use technical means, such as instrument is to obtain the data in the form of observations, likewise, recognition process can be a brain thinking, can also be algorithm is carried out. Based on the above basic understanding, a formal modeling of a recognition system to complete the recognition task is presented as shown in (1) below.

$$RS = S \circ R \tag{1}$$

In Formula (1), S stands for perception and R stands for recognition and identification process. In general, behaviors can be named according to people's subjective wishes, such as drinking water, eating, watching TV, etc. According to the above basic understanding of human behavior, when people perform specific behaviors, they will produce relatively significant external performance, which is defined as (2) below.

$$E = RA \longrightarrow O \tag{2}$$

In Formula (2), A represents the behavior set and O represents the external performance set. At this point, the framework designed is shown in Fig. 1 below.

As can be seen from Fig. 1, after obtaining various data related to human behavior through various sensing means contained in wearable sensor networks, these data need to go through a series of processing to identify the human behavior information contained therein. Although different types of perceptual data need different processing methods, the basic system framework is basically the same when considering the whole human behavior recognition system. Behavior recognition is often regarded as a special classification problem. A behavior recognition system conforms to the architecture of a typica pattern recognition system. The wearable sensor network at the bottom of the system is responsible for sensing all kinds of data related to human behavior, and transmitting the sensed data to the processing node through data communication

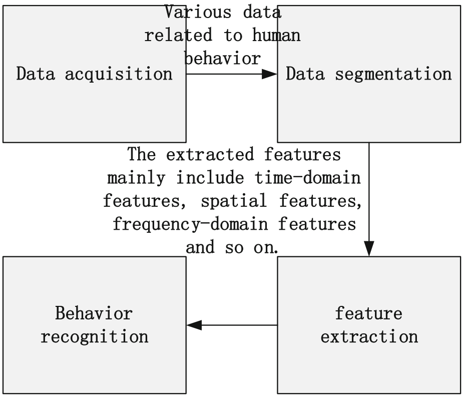

Fig. 1. Human motion recognition framework

technology [13, 14]. The obtained data is divided into a section of data, which can be called a behavior instance during behavior recognition. The data contained in a behavior instance is extracted to obtain the feature vector corresponding to the behavior instance as the input of the behavior recognition algorithm. The behavior recognition algorithm then recognizes the corresponding human behavior through the behavior model.

In the field of behavior recognition, the features extracted from acceleration data mainly include time domain features, space domain features, frequency domain features and so on. Let X be a sequence of acceleration readings obtained by segmentation, the specific contents and calculation methods of various features are as follows.

Time domain features include the mean, root mean square, variance, standard deviation, absolute mean difference, interquartile distance, mean crossing times of acceleration data in a period of time. The mean and root mean square describe the overall value of acceleration data. Variance, standard deviation, absolute mean difference, interquartile distance and mean crossing times all describe the fluctuation and dispersion of acceleration data from all aspects. The specific description of the above features is as follows: first, the mean value is calculated, and the calculation formula is shown in the following (3), followed by the root mean square (4) and variance (5), and the absolute mean difference (6) is as follows.

$$\overline{X} = \frac{1}{T}\sum_{t=1}^{T} x_t \tag{3}$$

$$RMS(X) = \sqrt{\frac{1}{T}\sum_{t=1}^{T} x_t^2} \tag{4}$$

$$\delta x = \frac{1}{T-1}\sum_{t=1}^{T} (x_t - \overline{X})^2 \tag{5}$$

$$MAD(X) = \frac{1}{T}\sum_{t=1}^{T} \left| x_t - \overline{X} \right| \tag{6}$$

In formulas (3)–(6), T represents time, x_t represents frequency domain, and the interquartile distance is used to describe the dispersion degree of acceleration data. The calculation method is to arrange the acceleration data from small to large, and calculate the difference between the third quartile and the first quartile. The mean crossing times is used to describe the fluctuation degree of acceleration data with time, and its calculation method is to count the times of acceleration data crossing the mean.

In addition to the above common features, there are also some features that can be used, such as maximum value, minimum value, histogram, etc. the spatial domain features mainly include the correlation coefficient of acceleration data of multiple axes. These correlation coefficients describe the degree of correlation between accelerations in different body parts and directions. Given two random variables representing accelerations of different axes, X and y, the correlation coefficient (x, y) between them can be calculated by formula (7).

$$correlation(X, Y) = \frac{\mathrm{cov}(X, Y)}{\delta x \delta y} \tag{7}$$

In formula (7), $\mathrm{cov}(X, Y)$ represents covariance and δx, δy represents standard deviation. Since the frequency domain characteristics are periodic, the calculation formula is as follows (8).

$$Energy(X) = \frac{\sum_{i=1}^{T} |F_i|^2}{T} \tag{8}$$

In formula (8), $|F_i|$ represents the amplitude after Fourier change. When processing environmental and physiological index data, the common features of sensor data including numerical types such as illumination, temperature, humidity and pulse also include simple time-domain features and frequency-domain features. The range of features used is basically covered by the previous section. Because the number of environmental and physiological sensors involved in a wearable sensor network is generally one sensor, the use of spatial domain features is rare. For speech signal, in addition to ordinary numerical calculation, speech recognition is also done to help mark the category of behavior.

2.2 Construction of Human Motion Recognition Model in Physical Education Based on Wearable Perception

Wearable sensor network, due to its rich types of sensors, can comprehensively sense all kinds of data related to human behavior, including acceleration, temperature, sound, location, object use, etc. at the same time, it has the advantages of small privacy invasion, small volume, light weight, small living interference, simple maintenance, etc., It has become a very advantageous technology of behavior perception. In a wearable sensor network composed of active sensor devices, people wear various types of sensor nodes, which are equipped with various types of sensors including acceleration, temperature, sound, light and so on. After the sensor node obtains the sensor reading, it sends the data to the sink node through wired, wireless and other communication methods. The sink node transmits the received data to the processing node for subsequent behavior identification. The advantage of active sensor equipment is that it has strong sensor ability and can sense various types of data. However, one of the obvious limitations is that active sensor devices need battery power to maintain their normal work. Therefore, a human motion recognition model for physical education teaching is constructed based on wearable perception.

The "quasi" mentioned above is the basic requirement to be met by a behavior recognition system, and its basic meaning is accurate behavior recognition. More specifically, when evaluating the functional indicators of a behavior recognition system, we try to carry out the evaluation with the help of confusion matrix. The confusion matrix is a square matrix. The rows in the matrix represent the recognition results. Based on the confusion matrix, many performance indicators described below can be calculated. Firstly, for the overall recognition accuracy, there are the following metrics. Recognition accuracy is one of the most commonly used performance indicators in behavior recognition. The definition of recognition accuracy is that the behavior instances correctly recognized account for the total number of all behavior instances. The recognition accuracy of the algorithm can be easily calculated on the basis of the confusion matrix. In addition to counting the recognition accuracy of the algorithm on the basis of examples, for the behavior recognition system whose input is continuous data flow, another common method of statistical accuracy is the time slice accuracy. Given a period of time series data, first slice it with a fixed length time slice, The essence of time slice accuracy is to calculate the proportion of correctly classified time slices.

For the identification of single person complex behavior, the following problem description is given: Based on the behavior data obtained by the perception platform, firstly segment the data to obtain the end behavior example. Considering the dynamics of behavior execution length, how to ensure the accuracy of data segmentation is the problem to be solved in this paper. Then, assuming that the system considers m behaviors, the problem to be solved in single person behavior recognition is to construct the recognition algorithm RA so that the recognized behavior category is equal to the corresponding real behavior category, considering various complex situations that human behaviors may include sequence, crossover and parallel execution in real life, The corresponding human behavior may be a single behavior executed sequentially, or a complex behavior composed of multiple basic behaviors executed alternately or in parallel. Due to the diversity of people's complex behaviors in daily life, it is impossible to show all kinds of complex execution of behaviors in daily life in training data. Therefore, it is necessary to design an algorithm framework that can identify complex human behaviors only by modeling and training basic behaviors.

Firstly, solve the problem of data source, complete the construction of single person behavior perception platform and obtain behavior data. On the obtained continuous sensor data stream, the data is segmented by using the 1-s sliding window segmentation technology to obtain the sequence of data units. After using classical methods to extract features from data units, the feature vector sequence is obtained. Based on the feature vector sequence, the sliding window model is used to segment and obtain behavior examples. Finally, the recognition algorithm based on EP and ESP, including sequential behavior model and complex behavior model, is used for recognition. In order to accurately segment the boundary between adjacent behaviors, the recognition results are used as feedback information to fine adjust the previous segmentation points.

In this process, how to model and identify sequential and complex behaviors is the biggest difficulty. To solve this difficulty, firstly, the problem of modeling and identifying the basic behavior of sequential execution is solved. Because of its strong ability to distinguish between categories and easy to understand, the classification method based on EP is more suitable for the use scenario proposed in this paper as a basic behavior modeling and recognition method. Considering the sequence characteristics of basic actions during behavior execution, in order to realize more accurate modeling of behavior, it is necessary to model the sequence of basic action elements in the behavior model. Therefore, based on the traditional EP method, the concept of ESP is proposed and used for behavior modeling. The complexity of single person behavior requires that the behavior model can model complex behaviors including sequential, cross and parallel execution. However, due to the diversity of complex behaviors, it is impossible to collect corresponding training examples for each complex behavior and model and identify them separately. Therefore, based on the basic behavior model of sequential execution, a training free complex behavior model acquisition method based on behavior length accumulation and optimistic score estimation is proposed. It realizes the goal of single person complex behavior recognition under diversified execution conditions without a large number of special training data.

After obtaining the perceived behavior data, the corresponding features are extracted from different types of data for recognition. One second of data is taken as a basic unit for feature extraction. Specifically, the extracted features include the following categories.

The features extracted from three-dimensional acceleration data include its mean value, variance, energy, entropy and correlation coefficient. Where the average value is the average value of acceleration over a period of time. Variance is used to characterize the stability of acceleration data. Energy characterizes the periodicity of acceleration data. The method of calculating energy is to calculate the square sum of the amplitudes of each component of the acceleration data after Fourier transform. Di is used to help distinguish different behaviors when the acceleration values of different behaviors have similar energy. The calculation method of Di is to calculate the average information Di of each component of acceleration data after Fourier transform. The correlation coefficient of acceleration is calculated by selecting the pairing between each axis of each acceleration sensor and calculating its correlation. The correlation coefficient is used to describe the correlation between the readings of axes in different directions of different acceleration sensors. In addition to the acceleration data, the average values of temperature, humidity and light intensity sensor readings are calculated as characteristics. For the micro RFID sensor worn by both hands, the article corresponding to the perceived tag is used as the characteristic value. When the tag is not perceived or the perceived tag reading error occurs, it is represented by null. For location data, the perceived room of the person is used as the characteristic value.

In general, a total of 75 features are extracted from the sensor data, of which 72 features are numerical, while the remaining three features (enumerative) can only be selected from several fixed values. For continuous sensor data flow, a 1-s sliding window is used to extract features, and every 1-s sensor reading is extracted into a 75 dimensional feature vector.

For numerical features, when the corresponding eigenvalues are extracted from the original data of the sensor, they need to be discretized for subsequent recognition. The discretization method based on the direct value is adopted. This method uses the category information to calculate the direct value of different discretized intervals, and selects the interval division method with the smallest direct value as the discretization method for continuous eigenvalues By using this method, the characteristics of 72 numerical types are discretized into 1046 disjoint intervals.

Firstly, the framework of single person complex behavior recognition algorithm based on EP is given. Given a new behavior observation sequence and assuming its time, the goal of the recognition system is to mark the observation value at each time with the correct category of one or more behaviors. Assuming that the current time is t, for each possible behavior a, first use a sliding motion with length L The window intercepts a section from the observed value sequence as an instance to wait for recognition, which is the average length of the behavior obtained from the training data. After obtaining an instance, calculate the possibility that the behavior category corresponding to the instance is a. after calculating the possibility for all possible behaviors, select the behavior with the highest possibility as the behavior corresponding to the current instance. Process After the current instance is completed, slide the sliding window forward and continue to process the next instance in a similar way. In order to accurately divide the boundary between two adjacent behaviors, a boundary detection and adjustment algorithm is proposed to realize the accurate segmentation of behavior boundary in the recognition process. The above processing steps will be executed repeatedly until the end of the input observation sequence.

In the process of recognition, the possibility of an instance corresponding to a certain behavior is estimated by calculating different scores. The method of calculating these scores is the core of this algorithm. In the algorithm, three different types of scores are proposed. The recognition model based on this is shown in (9) and (10).

$$E = \frac{\sum_{i=1}^{T} |F_i|^2}{correlation(X, Y)} \tag{9}$$

$$R = \frac{E}{correlation(X, Y)} \tag{10}$$

Given an instance of an observed value to be identified, the sequence of observed eigenvectors contains an instance of the behavior SA, followed by an instance of the behavior SA, starting at t time. During the recognition, the length Ls A of behavior SA is firstly used to intercept A section of observation value instance. In order to achieve accurate recognition, coverage score is introduced to measure the proportion of observation values unrelated to the current assumed behavior in A section of data.

2.3 Realize Human Motion Recognition

Combined with the sliding window based recognition algorithm and boundary detection algorithm proposed above, assuming that a sliding window contains a complete example of the current behavior, this combined algorithm can very effectively and accurately identify all behaviors in the data set to be identified. But in daily behavior, even if it is the same behavior, the time used by people to perform it may be different every time. As mentioned above, this difference in time length, if not effectively solved, will have a serious impact on the performance of the whole recognition system. Therefore, when designing the final behavior recognition algorithm, we need to further optimize this problem.

The search space of sequential pattern mining can be expressed as a tree structure. In this tree, each node represents a sequence pattern, and the sequence pattern represented by each node is the prefix of the sequence pattern represented by its child nodes. It is to mine new patterns by continuously expanding the sequential patterns in the current tree. Given a sequence pattern, there are two ways to extend it. Add a new item to the last element E of S. sequence extension adds a new element containing only one item after the last element E of S. For element extension, the items in each element are arranged in dictionary order. Only when a new element is arranged after all existing items, the item is considered to be added to the element. For example, for elements, e can be extended with item C, but e is not considered to be extended with a. The reason for this is to avoid duplicate sequences in the search process.

In the process of mining, esp miner traverses the search space through depth first search. For the support of sequences, it is obvious that the support of a sequence pattern is always less than or equal to the support of its subsequences. ESP miner uses this feature to preliminarily prune the search space. Starting from an empty sequence $< >$, esp miner continues to add new elements to the current sequence for expansion until the support of the new sequence pattern is lower than the minimum support threshold.

As a preliminary exploration of human behavior recognition based on wearable sensor networks, firstly, the method of human behavior perception and recognition using active wearable sensors with rich perception types and intuitive perception data is studied. From the problem of behavior recognition, this paper first selects the recognition of single person complex behavior as the research content. The problem of single person complex behavior recognition based on active wearable sensor networks is discussed in detail.

First, data acquisition. In a typical active wearable sensor network, the data collected by each sensor node is often sent to the sink node through a single hop wireless network, and then transmitted to the processing node for processing. When considering the problem of single person complex behavior recognition, the focus is on how to identify, and the problem of data acquisition can learn from the existing structure of typical wearable sensor networks. Therefore, on this issue, we do not make too much in-depth research on the problem of data acquisition.

Second, data segmentation. In the traditional behavior recognition system, sliding window is a widely used data segmentation technology. However, when considering practical application scenarios, it is found that it is difficult to accurately locate the boundary between two adjacent behaviors by using a simple sliding window model. Inaccurate data segmentation will lead to incomplete or mixed behavior data contained in a behavior instance, which will affect the effect of subsequent recognition. Therefore, when considering the problem of single person complex behavior recognition based on active wearable sensor networks, how to accurately segment the data is the key problem.

Third, feature extraction. In the field of behavior recognition, the commonly used sensor types based on active sensor devices include acceleration sensor, sound sensor and RFID sensor. The features used in the existing work include various time-domain and frequency-domain features of acceleration sensor data, various time-domain and frequency-domain features of sound sensor, and tag information of RFID sensor. In general, the sensors currently used and the features extracted according to the sensors basically cover various types of data that can be used under the conditions of the prior art. However, because human behavior recognition is a new topic, there is no final conclusion on what features extracted by each sensor can best reflect the behavior information contained in the data. The quality of the extracted features directly affects the accuracy of subsequent behavior recognition, so this is a problem worthy of in-depth exploration.

Firstly, the overall framework of espar algorithm is given. The input of the algorithm is the continuous observation data stream obtained from the human wearable sensor network, and becomes the sequence of feature vectors according to the preprocessing. The operation of espar algorithm is divided into two stages: model training and behavior recognition. In the training phase, the basic behavior data set executed in the order of marked behavior categories is used to train the model and mine the corresponding esp. In the recognition stage, given a sequence s of eigenvectors, s is segmented by using a sliding window with length LX to obtain an instance of behavior, where LX is the average length of behavior a that may correspond to the assumed current instance. After obtaining the instance, the recognition algorithm is used to identify the behavior corresponding to the instance. Corresponding to the data of two adjacent behaviors, the boundary detection algorithm is used to adjust their boundaries and adjust the length of behaviors, so as to achieve accurate behavior data segmentation and recognition. This process can be regarded as a feedback process. The purpose of this process is to correct the inaccuracy of the simple sliding window based method in behavior instance segmentation. The above identification process will be executed circularly until the whole input data is identified.

Based on the above definition, the complete process of espar algorithm is given. Firstly, for each possible behavior a, a sliding window is used to intercept a segment from the eigenvalue sequence as the behavior instance to be identified. The size of the sliding window is la. After obtaining the instance, calculate the possibility of the behavior using the specified method. Specify the most likely behavior as the behavior category for this instance. In order to correct the inaccurate behavior boundary caused by using a simple sliding window to segment data, a boundary detection algorithm is used to adjust the behavior boundary. The algorithm continues to cycle through the above process until the whole input is marked with a behavior category. The length of behavior has a great influence on the accuracy of recognition. Therefore, for ESP model, a fine adjustment method for sliding window size is also proposed.

3 Experiment

In order to verify the recognition effect of the human motion recognition method designed in this paper, it is compared with the research on Chinese elementary mathematical knowledge extraction based on CRF algorithm proposed in literature [11], and experiments are carried out.

3.1 Experimental Preparation

The performance of the proposed recognition method is verified by experiments. This experiment aims to measure the performance of the proposed method through recognition accuracy, verify the impact of different system parameter selection on the proposed method through model and parameter analysis methods, and highlight the effect of the proposed method through comparative experiments. The selected sports behavior list is shown in Table 1 below.

Table 1. List of sports behaviors

Number	Behavior
1	Walk
2	Run
3	High jump
4	Long jump
5	Basketball
6	Football
7	Skipping rope

As shown in Table 1, the sports behavior at this time has complex randomness, and subsequent identification method detection experiments can be carried out.

3.2 Experimental Results and Discussion

The action recognition of physical education teachers designed in this paper and the research on Chinese elementary mathematics knowledge extraction based on CRF algorithm proposed in literature [11] are used to detect the time spent in the above behavior. The detection results are shown in Table 2 below.

Table 2. Experimental results

Number	The identification method designed in this paper is time-consuming/s	The recognition method proposed in reference [11] is time-consuming/s
1	0.456	1.459
2	0.674	2.164
3	0.169	1.942
4	0.176	1.692
5	0.369	2.061

(*continued*)

Table 2. (*continued*)

Number	The identification method designed in this paper is time-consuming/s	The recognition method proposed in reference [11] is time-consuming/s
6	0.582	1.169
7	0.364	1.698

It can be seen from table 2 that the shortest action recognition time of physical education teaching people designed in this paper is 0.169 s. The human motion recognition method designed in this paper has good recognition effect, short time consumption, good recognition effect and certain application value.

4 Conclusion

This paper summarizes the fundamental problems to be solved in human behavior recognition. The basic structure of a behavior recognition system is proposed and the problem is subdivided. By reviewing the existing related work, it is found that the existing work has made some progress in behavior data acquisition technology, data segmentation technology, feature extraction and behavior recognition algorithm. These existing technologies have important guiding significance for the work. However, when it comes to the behavior recognition technology based on wearable sensor network and meeting the principle of "how fast and save", it is found that the discussion of human behavior in the existing work is still in the initial exploration stage, and there is no in-depth research on the complexity of human behavior, the interaction between multi-person behaviors and the real-time requirements of behavior recognition Systematic analysis and research.

Aiming at the recognition of single person complex behavior, this paper deeply discusses the sequential, cross and parallel execution of human behavior in daily life, puts forward a pattern matching algorithm with strong ability to distinguish between categories based on EP, and puts forward the basic behavior model of sequential execution, Through behavior length accumulation and optimistic score estimation, the complex behavior recognition algorithm framework including sequential, cross and parallel execution can be identified without additional training. At the same time, this paper further discusses the sequence of basic actions in people's daily behavior, puts forward a new pattern esp after serialization expansion for EP, and applies it to the above algorithm framework to effectively improve the recognition accuracy of the algorithm. A human behavior perception platform based on active wearable sensor network is designed and implemented. On this basis, a single person complex behavior recognition prototype system is implemented and applied to verify the above single person complex behavior recognition methods.

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